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A Conditional Value-at-Risk Based Planning Method for Integrated Energy System Considering Energy Storage System

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ABSTRACT

Owing to the potential higher energy supply efficiency and operational flexibility, integrated energy system (IES), including the power, gas, heating, and cooling systems, will be one of the primary forms of energy carrier in the future. However, with the increase of multiple energy devices and systems integration, IES planning is facing a significant challenge in terms of risk assessment. Therefore, a conditional value-at-risk (CVaR) based energy hub (EH) planning model is proposed in this paper. The numerical results illustrate the proposed method's effectiveness in balance the potential operation risk and investment cost, while the benefits of introducing energy storage system (ESS) are also verified.

Keywords: integrated energy system, energy storage systems, energy hub, conditional value-at-risk, planning method

NOMENCLATURE

Indices	
s	Index of scenario
y	Index of planning year
t	Index of hour in a scenario
i	Index of candidate device option
j	Index of candidate capacity option
n	Index of ESS type (h=heating, c=cooling, e=electric)
m	Index of energy type of EH (h=heating, c=cooling, e=electricity, g=gas)

Parameters	
α	Confidence level
β	Risk parameter
r	Amortization coefficient
k	Present-value coefficient
p_s	Probability of scenario s
dr	Discount rate
T	Lifetime
$I^{i,j}$	Investment cost of capacity j of device i
δ^n	Investment cost of ESS n module installed
pr	Input energy unit-price
λ	Maintenance unit cost
μ	Shedding load unit cost
$\mathcal{C}$	Coupling coefficient in EH
$P_{\max}$	Maximum input power
L	Load demand
$E_{\max}$	Maximum capacity of one ESS module
η^{ch} / η^{dis}	Charging/Discharging efficiency
Variables	
VaR	Value-at-Risk
$CVaR$	Conditional value-at-risk
$IC / TC / MC / LC$	Investment/trading/ maintain/load shedding cost
P	Input power
Q^g	Total gas consumption
Q^i	Total input energy of device i

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Q^n	Total charging and discharging mileage of ESS n
P^{ch} / P^{dis}	Charging/Discharging power
L^{SHED}	Shedding power
$L^{'}$	Output power of EH
$P_{\max}^{ch}$ / $P_{\max}^{dis}$	Maximum charging/discharging power
E	State of charge of ESS
$u^{i,j}$	Construction decision variable of capacity j of device i
$v^{ch,n}$ / $v^{dis,n}$	Charging/Discharging state of ESS n
Z^n	number of ESS n module installed

1. INTRODUCTION

Along with the increasing pressure on energy crisis and environmental pollution, the integrated energy system (IES) has attracted broad interests as different energy systems can be combined to achieve a higher energy supply efficiency and flexibility. Energy hub (EH) [1] is considered a group of energy facilities where the production, conversion, storage, and consumption of different energy carriers takes place, which is a promising option for IES planning. Energy storage systems (ESSs) [2] are vital in alleviating renewable energy and load fluctuations, which can provide other services as well, including peak shaving, uninterruptible power supply, as well as energy arbitrage. Thus ESS is an appropriate option for grid-scale energy storage applications. Moreover, it's predicted that the investment and operation costs of ESSs will become more affordable [3], which has also been proved by price data from the vendors. However, considering the difference between different types of energy, IES's planning still faces many difficulties and needs to be further studied.

Currently, several experts and scholars have carried out related research on the planning of IES. In [4], a two-stage robust optimization model is proposed to find an optimal solution to address the uncertainties of wind power output. In [5], an accurate reliability measure, i.e., expected unserved energy is used for electricity-gas system to optimize energy grids to reach higher social welfare. A multi-stage active distribution network planning model integrated with the application of energy storage system is presented in [6]. A bi-level planning method and design of an integrated energy system was introduced considering distributed generation, demand response, and energy storage system in [7].

However, these models and methods mainly focused on the co-optimization for investment and operation strategy, instead of the system risk management. Besides, the methods mentioned above have no unified standard for the consideration of system risk, and the definition of risk indexes is still not clear.

Based on the aforementioned literature review and essential needs in IES practice, in this paper, the Conditional Value-at-Risk (CVaR) approach is employed to model the risk caused by uncertainties in the IES scheduling problem. Based on the literature mentioned above review and essential needs in IES practice, in this paper, the Conditional Value-at-Risk (CVaR) approach is employed to model the risk caused by uncertainties in the IES scheduling problem. Thus, our main contribution is related to the CVaR method, which can measure risk effectively and optimize it along with the planning of an IES, producing a reliable, risk-averse planning scheme for decision-makers. Moreover, ESSs are introduced to improve operating flexibility. Therefore, an IES planning model is proposed to minimize the total cost, including the investment cost of facilities and CVaR considering operation, maintain and load shedding cost.

The rest of the paper is structured as follows: Section II presents CVaR to quantify potential risk loss, and the mathematical formulation of the planning model is shown in Section III. The numerical case study and its analysis are verified in section IV. Finally, conclusions are given in section V.

2. RISK MANAGEMENT FOR IES PLANNING: A CVAR-BASED APPROACH

To manage and illustrate risk, the daily scheduling problem is formulated as part of the objective function with a term measuring the risk based on CVaR. Value-at-risk (VaR) and CVaR are well-known risk measures in finance. CVaR, also known as Mean Excess Loss, Mean Shortfall, or Tail VaR, is considered to be a more consistent measure of risk than VaR [8]. It can be combined with analytical or scenario-based methods to optimize portfolios with large numbers of devices. CVaR and its minimization formula were first proposed in [9], which demonstrated numerical effectiveness through several case studies, including portfolio optimization. We consider a confidence level $\alpha \in (0,1)$, which in some real-world applications its value would usually be close to 1, e.g. $\alpha = 0.95$. At this confidence level, there is a corresponding VaR_α of the loss associated with a variable x defined as

$$VaR_\alpha = \zeta_a = \min\left\{\zeta \middle| \Psi(x,\zeta) \geq \alpha\right\} \tag{1}$$

When $\Psi(x,\cdot)$ is continuous and strictly increasing, ζ_a is simply the unique ζ satisfying $\Psi(x,\zeta) \geq \alpha$,

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ζ_a represents VaR in confidence level α. Where $\Psi(x,\zeta)$ is the distribution function for the loss $f(x,y)$, with $\Psi(x,\zeta)\to 1$ as $\zeta\to\infty$, i.e.

$$\Psi(x,\zeta)=P\{y|\,f(x,y)\le\zeta\} \tag{2}$$

$$CVaR_\alpha=\zeta_a+\frac{1}{1-\alpha}E\{[f(x,y)-\zeta_a]^+\} \tag{3}$$

$$[t]^+=\max\{0,t\}$$

In order to show that the VaR_α and $CVaR_\alpha$ of the loss $f(x,y)$ associated with a choice x can be calculated simultaneously, as did in original paper Rockafellar and Uryasev, 2000 in this subject. The $CVaR_\alpha$ of the loss related to a decision x is derived in (3), and the paper [9] persists the CVaR concept is articulated for general distributions.

Due to the limitations of VaR in the estimation of risk and the advantages of CVaR compared with VaR, the risk management in this study is addressed by CVaR. Unrelated scenarios can be considered as different portfolio products in IES planning, considering the electricity/gas consumption cost, maintain cost, load shedding cost, etc. CVaR quantifies the average loss over a specified period of unlikely scenarios beyond the confidence level. For example, a one-day 99% CVaR of $12 million means that the expected loss of the worst 1% scenario over one day is $12 million.

3. MODEL FORMULATION

Based on the expression of CVaR in Section II, an IES planning model is presented, which comprehensively considers combined cooling, heating, and power (CCHP), gas boiler (GB), air conditioner (AC), battery energy storage system(BESS), thermal energy storage system (TESS), and cold energy storage system (CESS). It can serve for the planning of IES in terms of both economy and risk management.

3.1 Objective function

The objective function of the proposed model is to minimize the total cost considering investment cost, trading cost, maintain cost, and load shedding cost, denoted by (4)-(14).

$$\min\left\{\begin{matrix} IC \\ +\left[(1-\beta)\sum_s p_s\left(TC_s+MC_s+LC_s\right)+\beta CVaR_\alpha\right]\end{matrix}\right\} \tag{4}$$

$$IC=\sum_i\sum_j r^{i,j}I^{i,j}u^{i,j}+\sum_n r^n\delta^n Z^n \tag{5}$$

$$r^{i,j}=\frac{dr(1+dr)^{T^{i,j}}}{(1+dr)^{T^{i,j}}-1} \tag{6}$$

$$r^n=\frac{dr(1+dr)^{T^n}}{(1+dr)^{T^n}-1} \tag{7}$$

The first term in total cost (4) of IES denotes the investment cost with amortization coefficient (6)-(7) to amortize over their lifetime, which consists of all devices' candidate investment options and all ESSs' in (5). The second term represents the trade-off between scheduling cost and expected risk, where β and α are the risk parameter and confidence level, respectively, and their values are between 0 and 1. If the value of β is closer to 1, the significance of the risk factor, namely CVaR, increases.

$$TC=\sum_s p_s TC_s=\sum_s p_s(\sum_{t=1}^{24} pr_t^e P_{s,t}^e+pr^g Q_s^g) \tag{8}$$

$$P_{s,t}^e=\sum_i\sum_j P_{s,t}^{i,j,e} \tag{9}$$

$$Q_s^g=\sum_{t=1}^{24}\sum_i\sum_j P_{s,t}^{i,j,g} \tag{10}$$

$$MC=\sum_s p_s MC_s=\sum_s p_s(\sum_i\lambda^i Q_s^i+\sum_n\lambda^n Q_s^n) \tag{11}$$

$$Q_s^i=\sum_j\sum_{t=1}^{24} P_{s,t}^{i,j} \tag{12}$$

$$Q_s^n=\sum_{t=1}^{24}(P_{s,t}^{ch,n}+P_{s,t}^{dis,n}) \tag{13}$$

$$LC=\sum_s p_s LC_s=\sum_s\sum_m\sum_{t=1}^{24} p_s\mu^m L_{s,t}^{SHED,m} \tag{14}$$

In the superscript on the upper right corner, g, h, c, e represents different energy forms: natural gas, heat, cold, and electric, respectively. Trading cost (8) consists of electricity consumption cost (9) and gas consumption cost (10) of all facilities in each scenario. Maintain cost (11) is related to input power of each devices and charging/ discharging mileage of ESS, which is denoted by (12) and (13), respectively. Load shedding cost (14) is calculated by multiplying shedding load unit cost with the summation of shedding load power.

$$CVaR_\alpha=VaR_\alpha+\frac{1}{1-\alpha}\sum_s p_s\left[TC_s+MC_s+LC_s-VaR_\alpha\right]^+ \tag{15}$$

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$CVaR_{\alpha}$ denotes the loss expectation of the detected scenarios derived from (3) with the auxiliary variable VaR_{α} in (15). If the amount of α is supposed to be equal to 0.95, the $CVaR_{0.95}$ considers the expectation of 5% with the highest cost.

3.2 Constraints

$$\begin{bmatrix} L_{s,t}^{e'} \\ L_{s,t}^{h'} \\ L_{s,t}^{c'} \end{bmatrix} = \sum_i \sum_j \begin{bmatrix} C^{i,j,ee} & C^{i,j,eg} \\ C^{i,j,he} & C^{i,j,hg} \\ C^{i,j,ce} & C^{i,j,cg} \end{bmatrix} \begin{bmatrix} P_{s,t}^{i,j,e} \\ P_{s,t}^{i,j,g} \end{bmatrix} \tag{16}$$

$$0 \le P_{s,t}^{i,j,e} \le u^{i,j} P_{\max}^{i,j,e} \tag{17}$$

$$0 \le P_{s,t}^{i,j,g} \le u^{i,j} P_{\max}^{i,j,g} \tag{18}$$

$$0 \le L_{s,t}^{SHED,m} \le L_{s,t}^{m} \tag{19}$$

According to the energy hub theorem, the energy coupling matrix equations is constructed, as shown in (16). Constraints (17) and (18) model the binary variable, which is equal to 1 if the devices' candidate option is available, being 0 otherwise. Constraint (19) represents the shedding power is subject to the upper limit total load.

$$v_{s,t}^{ch,n} + v_{s,t}^{dis,n} \le 1 \tag{20}$$

$$0 \le P_{s,t}^{ch,n} \le v_{s,t}^{ch,n} Z^n P_{\max}^{ch,n} \tag{21}$$

$$0 \le P_{s,t}^{dis,n} \le v_{s,t}^{dis,n} Z^n P_{\max}^{dis,n} \tag{22}$$

$$0 \le E_{s,t}^{n} \le Z^n E_{\max}^{n} \tag{23}$$

$$E_{s,t+1}^{n} = E_{s,t}^{n} + (P_{s,t}^{ch,n} \eta^{ch,n} - P_{s,t}^{dis,n} / \eta^{dis,n}) \Delta t \tag{24}$$

$$E_{s,0}^{n} = E_{s,24}^{n} = 0 \tag{25}$$

Constraint (20) ensures that the ESSs cannot be charged and discharged at the same time. Charging/discharging power of ESSs are limited by the power of investment option in (21)-(22), in which upper bounds is denoted by integer variable Z^n, the number of ESSs module and binary variable $v^{ch,n} / v^{dis,n}$, denoting the charge/discharge status. Constraint (21) and (22) denote the relationship between charge/discharge power and SOC (state of charge). Constraint (24) represents the limitation of energy capacity for ESSs. Constraint (25) ensures the initial and final values of SOC in one day are the same.

$$L_{s,t}^{e} + P_{s,t}^{dis,BESS} = L_{s,t}^{e'} + P_{s,t}^{ch,BESS} + L_{s,t}^{SHED,e} \tag{26}$$

$$L_{s,t}^{h} + P_{s,t}^{dis,TESS} \le L_{s,t}^{h'} + P_{s,t}^{ch,TESS} + L_{s,t}^{SHED,h} \tag{27}$$

$$L_{s,t}^{c} + P_{s,t}^{dis,CESS} \le L_{s,t}^{c'} + P_{s,t}^{ch,CESS} + L_{s,t}^{SHED,c} \tag{28}$$

Constraints (26)-(28) are the power balance between demand and supply. It should be noted that, the supply and demand of electric load should be strictly equal, while the heat and cold load can be appropriately relaxed based on real-world applications.

4. CASE STUDY

The proposed model is applied to an EH in Fig 1 . This EH is used to simulate an industrial park with electricity, heat, and cold load as well as electricity and natural gas input. Dotted lines mean they are investment options to be planned and connected. Case data including construction costs, devices' types, capacities, load scenarios can be found in Ref [10].

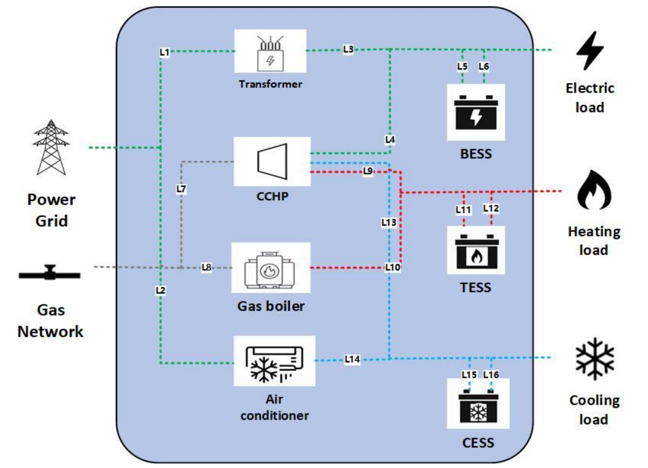

Fig 1 Energy hub model studied in the case

To illustrate the rationality of the proposed model, the annual discount rate is set as 5%, and the annual growth rates of electricity, heat, and cold load are 5%, 3%, and 2%, respectively. The operation scenarios are considered hour-by-hour, while K-means clustering is used in scenario reduction, reducing the scenarios from 3650 to 100 days to avoid a heavy computational burden. YALMIP toolbox in MATLAB R2019b is used for modeling and Gurobi 9.0.0 optimizer for solving.

4.1 Analysis of investment strategies

To address different investors' risk preferences, different values of risk parameters are considered. In general, we consider investors with risk parameters higher than 0.5 as “risk-averse investors”, investors with risk parameters lower than 0.5 as “risk-seeking investors”, investors with risk parameters equal to 0.5 as “risk-neutral investors”. In the objective function (4), the decision variables of investment terms are $\{u^{i,j}, Z^n\}$ which limit the operation bounds of devices and ESSs. We traced points and fitted a curved surface in Fig 2 where the total costs vary with risk parameters β and confidence levels α. The value of the risk parameter

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β represents the degree of investor aversion to risk, and the confidence level α describes the probability threshold of the expected loss $CVaR_{\alpha}$.

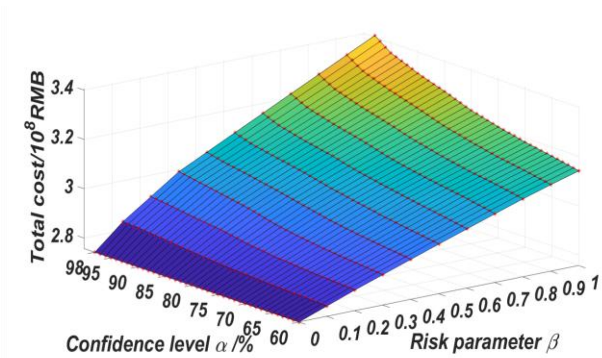

Fig 2 Total cost and changes in different confidence level and risk parameter

The fitting surface of the total cost, confidence level, and risk parameters are close to a plane. With investors become more "risk-averse" and higher certainty requirements are needed for capital investment results, the total cost increases almost linearly. This figure can be used as an investment reference to provide a rough investment interval for different investors. In addition, we explored the investment cost variation of varying confidence levels and risk parameters to analyze the investment strategy in Fig 3 further.

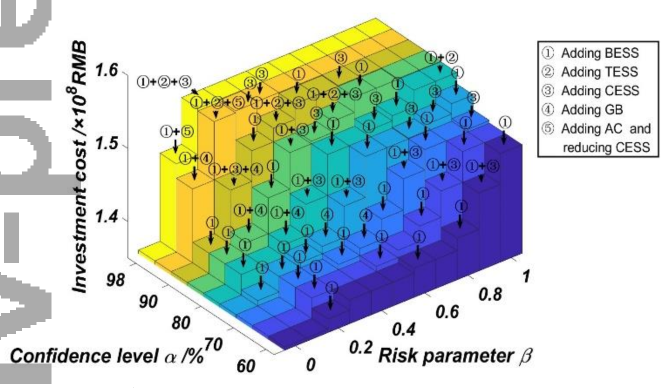

Fig 3 Investment strategies and changes in different confidence level and risk parameter

In Fig 3, BESS is preferred to be invested because of its arbitrage from electricity price policy and increment in system flexibility. Under more risk-averse and higher certainty requirements, More ESSs including BESS, TESS, and CESS is chosen rather than energy-supply facilities {CCHP, GB, AC} with higher capacity, to strike a balance between its arbitrage and construction cost. The figure can be used as an auxiliary tool to provide tailor-made investment advice for different investors.

4.2 Analysis of daily schedule with and without ESSs

In this section, we select risk-neutral ($\beta = 0.5$) and a certain confidence level ($\alpha = 0.95$) to analyze the planning strategy and compare the electricity power dispatch with peak-valley electricity tariff policy with and without BESS in Table 1 and Fig 4.

The results show that: in the case where no BESSs are allowed to be installed (a), the CCHP is operated at a low

Table 1 Comparison of investment cost with and without ESSs (β=0.5, α=0.95)

Cost (×10^4RMB)		without ESS	with ESS
IC	CCHP	12000	10000
	GB	900	900
	AC	1500	1200
	Transformer	1000	1000
	BESS	-	1820
	TESS	-	19
	CESS	-	315
	Total	15400	15254
CVaR		19182.36	18788.09
Total		31615.19	31353.41

power level during valley-load hours at nights and at rated power during peak-load hours in the day. Most of the rest power is supplied by the transformer with electricity traded from the bulk power system. However, load shedding (denoted by red color) still exists from 12:00 to 17:00. The situation is much improved with the installation of BESSs in (b). BESS is charged from 1:00 to 7:00 during valley-load hours with low electricity price, and then discharges from 11:00 to 22:00 in peak-load hours with high electricity price. Benefiting from BESSs, there is only a small amount of load shedding at 21:00.

5. CONCLUSIONS

This paper proposes an IES planning model based on CVaR. By introducing the CVaR theorem, a planning method with the risk evaluation index to calculate the potential loss in balance the operation risk and investment cost is proposed. The case results show that considering ESSs in IES planning can effectively increase energy arbitrage profits, and reduce load shedding. Therefore, CVaR, as a portfolio method in finance, can be utilized as a method that can serve for both planning and operation in IES.

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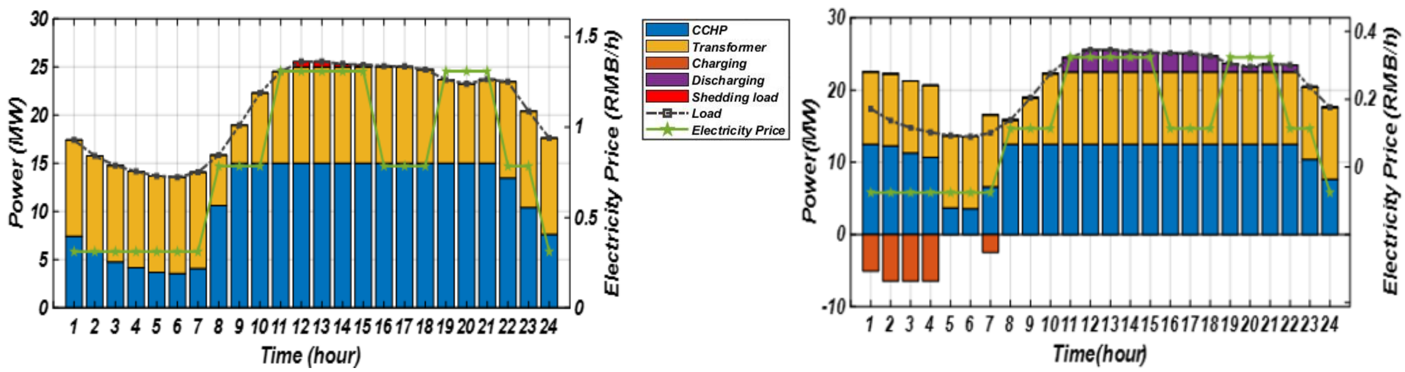

(a) (b)

Fig 4 The hourly electricity schedule in a scenario: (a) without BESSs (b) with BESSs

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